

INTRODUCING CONNECTIVITY ANALYSIS TO NEUROIS RESEARCH

Completed Research Paper

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Abstract

The integration of both neuroscience and psycho-physiological methods into Information Systems (IS) research in order to better understand how the brain operates in an IS-relevant context has gained importance. Articles highlighting the potential of NeuroIS have opened the discussion of methodological issues associated with the use of fMRI. NeuroIS research, however, must remain cognizant of the fact that the neural implementation of complex mental processes is based on activity in a network of varied brain areas. Against this background, the present article seeks to make a methodological contribution by introducing methods of connectivity analysis to IS research and by giving an overview of the basic principles. We describe different methods of connectivity analysis, discuss a concrete example, and show how connectivity analysis can inform IS research. The major objective of this paper is to contribute to a better understanding of advanced techniques for brain imaging data analysis.

Keywords: Neuroscientific research, NeuroIS, functional Magnetic Resonance Imaging (fMRI), connectivity analysis, behavioral science, cognition/cognitive science, data analysis, method

Introduction

Information Systems (IS) research in the last few years has revealed the growing importance of integrating neuroscience and psycho-physiological methods and tools into the research. The objective is to better understand how the brain operates in an IS-relevant context (e.g., human-computer interaction), often studied based on functional Magnetic Resonance Imaging (fMRI) (Dimoka et al. 2010; Dimoka et al. 2011; Riedl et al. 2010a). This new field of research is referred to as NeuroIS, and is defined as the “idea of applying cognitive neuroscience theories, methods, and tools to inform IS research” (Dimoka et al. 2007). The aim of NeuroIS research is to develop new theories that are able to predict IT-related behaviors, and to design IT-artifacts in ways that positively influence variables such as productivity or satisfaction (Riedl et al. 2010a). The application of neuroscientific theories, methods, and tools has the potential to significantly advance IS theorizing and to facilitate scientific process in the IS discipline (Dimoka et al. 2010; Dimoka et al. 2011; Riedl et al. 2010a).

Various theoretical and conceptual papers have defined the field of research, have identified promising research areas for NeuroIS (Dimoka et al. 2012; Riedl et al. 2010a), have suggested opportunities for ways in which IS researchers can apply neuroscientific tools to better understand IS phenomena (Dimoka et al. 2011; Riedl 2009), and have put forward a general discussion of the potential and the challenges of NeuroIS (Dimoka et al. 2007; Riedl et al. 2010a). As well, a number of empirical studies apply fMRI to inform IS research (Dimoka 2010; Dimoka and Davis 2008; Riedl et al. 2010b, 2011). For example, Dimoka (2010) used fMRI to investigate neural correlates of trust and distrust. She showed that trust and distrust are associated with the activity of different brain areas, thus providing evidence of trust and distrust as distinct constructs that are associated with various neurological processes. Riedl et al. (2010b) used fMRI to demonstrate neural differences between women and men with regard to their perception of eBay websites that have varying levels of trustworthiness. Furthermore, Dimoka and Davis (2008) identified brain activity patterns associated with determinants of the Technology Acceptance Model (TAM) to show how the application of fMRI can increase understanding of IS theories and models. Finally, Riedl et al. (2011) investigated brain activity patterns during human-avatar interaction, as well as corresponding trust behavior.

Both empirical and theoretical articles indicate that this interdisciplinary approach is up to date and that it has the potential to yield important findings for IS research. Recent publications have already begun to discuss methodological issues associated with the use of fMRI for IS research (Dimoka et al. 2011; Dimoka 2012). Undoubtedly, prosperous development of the field of NeuroIS necessitates expansion and deepening of the methodological discussion. Another factor to consider is that the existing empirical fMRI studies typically contrast brain activity in one experimental condition against brain activity in another condition (e.g., trustworthy versus untrustworthy websites). This approach is important in order to gain insight into the nature of specific IS constructs such as trust (Dimoka 2010; Riedl et al. 2010b) or TAM determinants (Dimoka and Davis 2008). NeuroIS research, however, must be cognizant of the fact that the brain functions as a complex network of regions that are connected both anatomically and functionally. Studies in the recent neuroscience literature that consider brain connectivity reflect the development of the area of research (e.g., Friston 2002; Friston et al. 2011; Hare et al. 2010; Heim et al. 2009), but the pioneering fMRI studies in NeuroIS have not done so. These neuroscience articles not only contrast one experimental condition against another in order to identify neural activity changes, but they also analyze the connectivity (correlation or causality) between specific brain areas. With consideration of these developments in the brain sciences, NeuroIS research should also be open to the neuroscientific advancements, in order to maximize the information extracted out of fMRI data.

Against this background, the present article makes a methodological contribution that is in line with the few existing studies (Dimoka 2012), yet furthers the research by taking a first step in introducing different methods of connectivity analysis to IS research. The aim is to enable NeuroIS researchers to apply recent neuroscientific methods and tools to NeuroIS research. Therefore, we first give a brief overview of the basic principles of connectivity analysis. Second, we describe different methods and forms of the ways in which connectivity analysis can be conducted. Third, we use an already published data set that contains data about trustworthiness perceptions of eBay offers (Riedl et al. 2010b), thereby providing a concrete example and showing how connectivity analysis can inform IS research. However, we do not focus on the development of new trust-related theories. Rather, we seek to demonstrate the additional benefit that

connectivity analysis can offer in order to broaden the methodological focus in IS research. We address these topics because we believe that using neuroscientific concepts and methods can add a new theoretical perspective to IS research and management (e.g., Dimoka et al. 2011; Riedl et al. 2010a/b; Weber and Johnson 2009), a view that is also held by other IS researchers such as Benbasat et al. (2010), who write: “[T]he direct measurement of brain activity [...] may be transformative, both to the study of trust and also to the IS discipline as a whole” (p. 368).

The potential and additional benefit of connectivity analyses for NeuroIS research are evident in the context of a research question that we selected due to its importance in IS research (Riedl et al. 2010b): Is online trust associated with activity changes in certain brain areas, and do these activity changes lead to altered trustworthiness perceptions (Riedl et al. 2010b)? For IS research, it is interesting to study the neural effects caused by the perception and processing of information provided on a user interface (e.g., website), as engaging in a trust decision has been demonstrated to trigger activity in several regions of the trustor’s brain (for a review, see Riedl and Javor 2012). FMRI studies have contrasted brain activity in different experimental conditions in order to identify specific brain areas related to constructs such as reward, uncertainty, and memory. From this kind of research we do know how to determine which brain regions are probably involved in trust decisions. What we do *not* know, however, is how these specific brain areas, the neural correlates of trust and distrust, interact or work together. Yet such an understanding is important, because mental processes that are relevant in IS research are higher-order constructs rather than basic perceptual processes. Thus, IS constructs are typically based on activity in multiple brain areas, and not only in one single brain region. Connectivity analysis, which addresses this methodological challenge, can be defined as a method for identifying (i) correlations between regionally separate brain areas (functional connectivity) or (ii) the influence of one or more regionally separate brain areas on another (effective connectivity).

Basic Principles of Connectivity Analysis

Using fMRI helps to investigate the function of the human brain along two dimensions: functional specialization and functional integration (Figure 1). The concept of *functional specialization* assumes that local brain areas are specialized in certain aspects of information processing. Functional specialization also stresses the possibility of finding this specialization in anatomically separate areas of the brain (Marshall and Fink 2003). To date, the brain imaging studies conducted in NeuroIS research are based on exactly that concept (e.g., Dimoka 2010; Riedl et al. 2010a). Brain areas activated due to a certain task are interpreted as elements of a distributed system. For example, Brodmann Areas (BA) 8 and 9 (dorsolateral prefrontal cortex), as well as BA 10 (ventromedial prefrontal cortex), are summarized under the label of the prefrontal cortex, which is an area known for its central role in decision making and emotion regulation, and which, therefore, is a critical region for IS research (Dimoka et al. 2011; Riedl 2009).

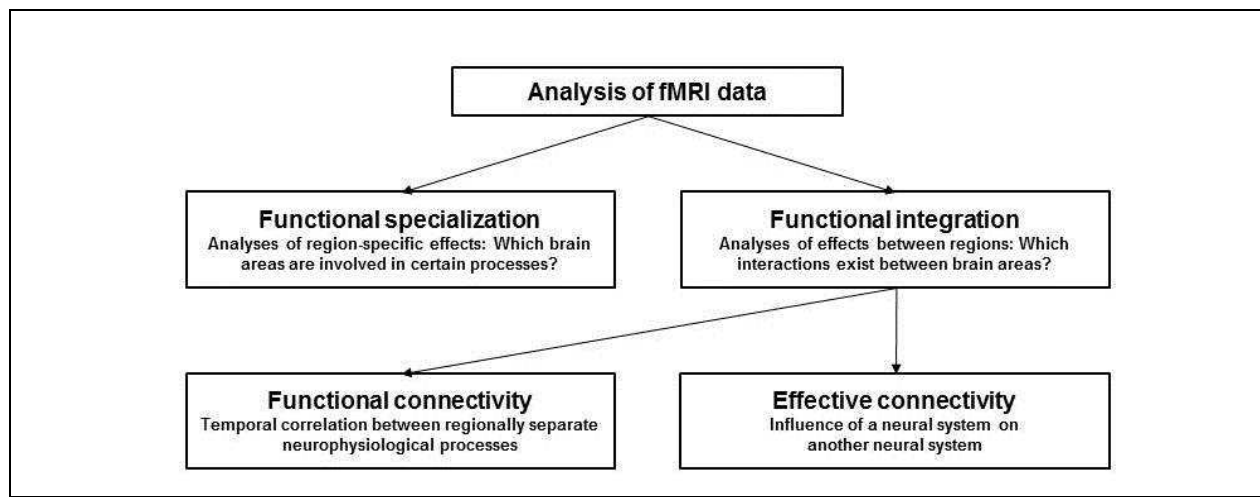
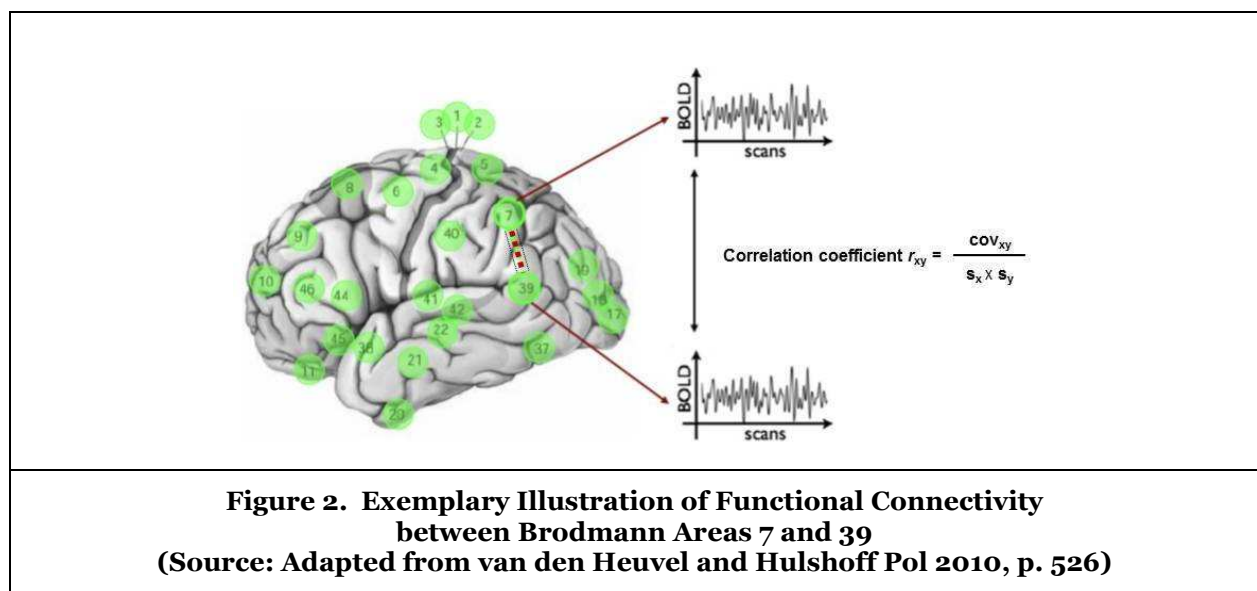


Figure 1. Analysis Categories for fMRI Data (Source: Based on Friston 1994, p. 58)

Against this background, functional specialization lacks the opportunity to describe how distributed brain areas work together through context-dependent coupling as a functional entity. It is not possible, therefore, to address the question of how brain areas work together in terms of a network. However, this question is addressed by *functional integration* (Friston 2002). Currently, two forms of functional integration can be distinguished, namely functional connectivity and effective connectivity. Functional connectivity describes statistical dependencies between a time-series of activity of neurons or neuronal populations. In contrast, effective connectivity is based on an a priori defined model, describing the emergence of the observed data.

Functional Connectivity

The definition of functional connectivity implies that it works with every statistical procedure that is available for describing dependencies between separate time-series. As an example, functional connectivity between two brain areas (x and y), can be described based on Pearson's product moment correlation between these time-series (Figure 2; exemplary shown between BA 7 and BA 39).



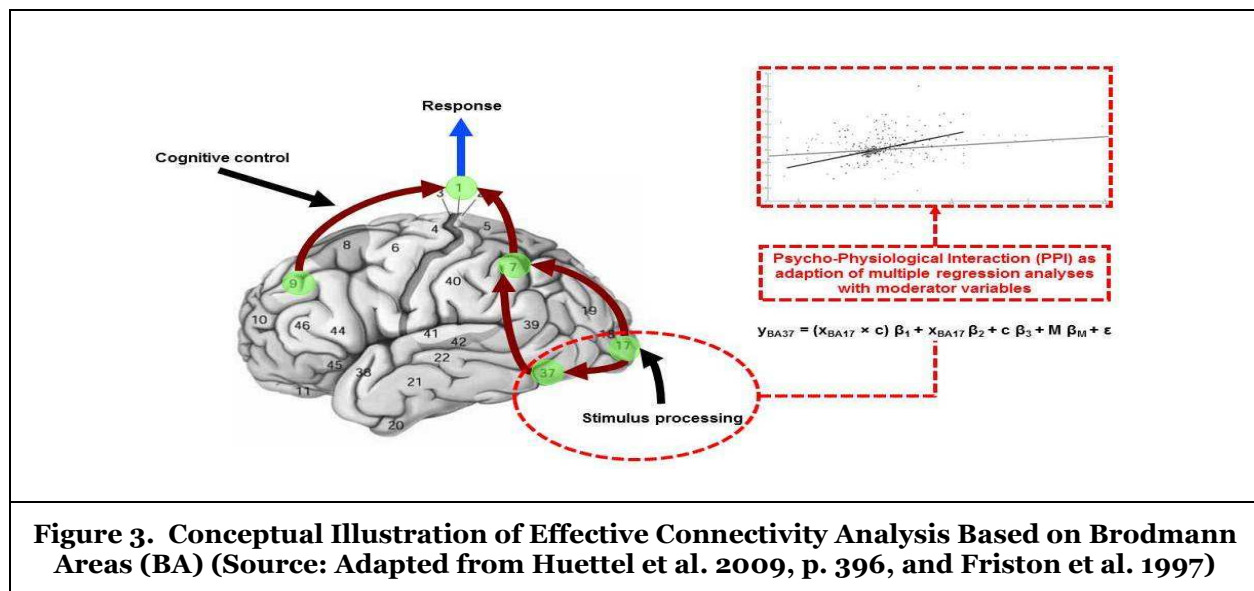
It is important to note that analyses of functional connectivity suffer from the same interpretation problem as correlations. When two correlating time-series are found, which indicates functional connectivity, several interpretations are possible: (1) BA 7 is influenced by BA 39, (2) BA 39 is influenced by BA 7, (3) both BA 7 and BA 39 influence each other, or (4) both are influenced by activation in another brain area. These different interpretations can only be distinguished by a model of causal influences of the time-series—that is, by a model of effective connectivity.

Nevertheless, models of functional connectivity can exceed pure correlations between time-series. For example, there are multivariate techniques that enable the identification of groups of voxels, which correspond to time-series of orthogonal (Friston et al. 1993) or statistically independent (Beckmann et al. 2005) components of an fMRI data matrix (such a matrix is a representation of measured fMRI data in two-dimensional form, voxels by time-points; see Huettel et al. 2009). One interpretation problem persists, however: The results of functional connectivity analyses consist of complex patterns in either case, and the formation of these patterns can be explained in multiple ways. Based on this reasoning, functional connectivity analyses are not suited for every research question. They are a sound choice when there is little knowledge about the neural system that is the focus of a study, which implies that ex ante models are not available.

Returning to our initial research example regarding online trust, we conclude that functional connectivity analysis can shed light on the question of whether activation differences in (for example) structures associated with memory correlate with activation differences in (for example) structures associated with uncertainty. As we can rely on existing reviews regarding the importance of activation differences in the case of these structures and their role in trust decisions (Riedl and Javor 2012), we might want to go one step further and hypothesize that activation differences in structures associated with memory might influence whether or not activation differences occur in structures associated with uncertainty. Assessment of a hypothesis such as that would require effective connectivity analyses.

Effective Connectivity

Effective connectivity describes a causal influence that a neuronal population exerts on another (Friston 1994). Alternatively, it can be said that effective connectivity in a neuronal system corresponds to the simplest circuit resembling the observed activation patterns of the neurons under examination (Aertsen and Preißl 1991). Both descriptions emphasize the need for inferences about such an influence or activation pattern to be model-based. It follows that causal conclusions on the basis of effective connectivity analysis depend on the reliability of the applied model. Depending on the specific research questions and assumptions addressed, different models (referred to as mechanistic models) can be applied. These models use mathematical operations to describe causal relationships in complex systems (Figure 3).



The illustration in Figure 3 (left side) conceptually illuminates the principle of effective connectivity based on fMRI. Researchers define a model of functional dependencies between different brain areas in a first step. A critical point is that this model has to be based on knowledge regarding structural relationships between these brain regions that is already available. The hypothetical example in Figure 3 shows that the model can include both direct (BA 17 to BA 7) and indirect (BA 17 to BA 37 to BA 7) connections between brain areas. Moreover, external stimuli or cognitive states might exert direct influence on (a) activity in a certain area (e.g., visual stimulus processing influences activity in BA 17) and/or (b) a specific connection between areas (e.g., increased cognitive control might lead to an elevated influence of BA 9 on BA 1).

For the sake of better exemplifying the mathematical modeling of connectivity analyses, the right side of figure 3 (red dashed lines) presents the basic statistical principle underlying Psycho-Physiological Interaction (PPI). The equation in Figure 3 (see lower right corner) shows that effective connectivity in the form of PPI between two areas x and y can be described by multiple regression analyses with moderator variables.

Within a simple bilinear model, regression analyses characterize the influence of a voxel x (in BA 17) on a voxel y (in BA 37), dependent upon the stimulus input (e.g., trustworthy offer: yes or no; represented by c in the equation in Figure 3). Thereby, the context-dependent coupling corresponds to the difference between regression lines at the separate regression of y on x under two different conditions. In addition to the interaction term ($x_{BA17} \times c$, that is, times-series \times context [stimulus]), the multiple regression equation contains at least the main effect of the stimulus input c and the time-series of x . It is possible to add additional experimental factors or covariates (e.g., movement parameters; exemplary shown as $M \beta_M$ in the equation in Figure 3).

The entire equation can be implemented as a general linear model, so that the coupling hypothesis for the chosen region x can be analyzed for every voxel in the brain using standard fMRI analysis software. Therefore, PPI can be described as an explorative method to determine effective connectivity. At this point it is important to note that we explain a simple and conceptual example of effective connectivity using PPI because of the introductory nature of this paper and the following practical examples. Further statistical procedures for other effective connectivity analyses are given in the continuative literature presented in Table 1. As well, it is crucial to recognize that effective connectivity can be represented by a large number of mathematical models.

Major Steps in Connectivity Analysis for NeuroIS Research

Dimoka et al. (2012, p. 694) state directly that “it is important to clarify that NeuroIS is not a panacea for all IS research issues.” Nevertheless, the comprehensive overview outlined in this paper entitled “On the Use of Neurophysiological Tools in IS Research: Developing a Research Agenda for NeuroIS” (Dimoka et al. 2012) gives helpful avenues for further IS research that integrates neuroscientific methods and tools. Against this background, the major steps in connectivity analysis for NeuroIS research can be interpreted as a progression that IS researchers might follow when applying NeuroIS methods. Assuming that a comprehensive fMRI data analysis based on a specified research question is planned, the steps can be outlined as follows:

- (1) Performance of activation analysis: Usually, this is the first step of any image analysis (Friston et al. 1994; Friston et al. 1995). Although it seems reasonable to assume regions that are showing similar activity changes between tasks may also be part of the same functional network, this is by far not a certainty (Stephan 2004). Within a typical mode of activation analysis, a univariate approach is used. It may be preferable, however, to use a multivariate approach when research is attempting to identify cohesive networks. These multivariate approaches are characterized by greater sensitivity, making explicit use of relationships among measured variables (Lukic et al. 2002).
- (2) Relation of brain activity to behavioral variables: Notwithstanding the problems related to the correlation of brain activity with behavioral variables (Vul et al. 2009), many researchers relate brain activity patterns to either performance variables measured during the experiment, or to demographic measures (e.g., gender in Riedl et al. 2010b). The integration of performance variables, in particular, may be considered to be the completion of a causal chain (stimulus perception \rightarrow brain activity pattern \rightarrow behavioral response in the form of task performance). In this sense, connectivity analyses provide an anchor for interpretation and confirm that the patterns of activity make a difference in performance.
- (3) Analysis of functional connectivity or effective connectivity: The simplest approach to assess functional connectivity is calculating pairwise correlations. Based on such calculations, the resulting estimates can be compared across tasks or groups to define dependencies at the group level. Effective connectivity requires a more focused, and thereby more complex, approach, wherein certain regions are identified a priori and tested within detailed models afterwards.

In this context, it is important to note that connectivity analyses can be seen as an enhancement of earlier fMRI studies looking at single, regionally separate areas. Obviously, the final choice of connectivity analyses (functional or effective) depends upon the specified research question. Functional connectivity analyses are reasonable when the goal is a first exploratory look at the activation patterns. If research questions embrace directed influences, analysis of effective connectivity would be needed. As the field of

NeuroIS research is in its infancy, this implies that connectivity analyses are reasonable when a first contrast of brain activity of one condition against the brain activity of another condition already exists.

An Overview of Techniques in Connectivity Analyses

Research is currently seeing rapid methodological developments in the estimation of functional and effective connectivity—an observation readily confirmed by a look into recent issues of neuroscience journals such as *NeuroImage* and *Human Brain Mapping*. Table 1 characterizes major methods used for estimating functional and effective connectivity, and suggests further readings. This list provides an overview of important approaches relevant to IS research. However, the list is illustrative rather than exhaustive.

Table 1. Major Methods in Connectivity Analysis		
	Brief description	Suggested readings
<i>Functional Connectivity</i>		
Principal Component Analysis (PCA)	PCA to summarize complex patterns of interregional correlations. Helpful method to follow up from the calculation of pairwise correlations.	Andersen et al. 1999; Baumgartner et al. 2000; Viviani et al. 2005
Independent Component Analysis (ICA)	Newer method than PCA; powerful for extracting resting state networks in fMRI data. Not assuming orthogonality, but rather maximal independence.	Beckmann et al. 2005; Calhoun et al. 2001; McKeown and Sejnowski 1998
<i>Effective Connectivity</i>		
Psycho-Physiological Interaction (PPI)	Adaption of multiple regression analysis with moderator variables. Building on a simple bilinear model that characterizes the influence that a specific region has on another region, dependent on a certain cognitive context or experimental condition. An explorative method to determine effective connectivity, not demanding an a priori model.	Banks et al. 2007; Friston et al. 1997; Gitelman et al. 2003; White and Alkire 2003; Williams et al. 2006
Structural Equation Modeling (SEM)	Multivariate, hypothesis-driven method adapted for fMRI-analyses. Based on a structural model, representing a hypothesis about the relationships between several variables.	Bullmore et al. 2000; Büchel and Friston 1997; Friston et al. 2003; McIntosh et al. 1994; Penny et al. 2004
Dynamic Causal Modeling (DCM)	Represents the most complex model of effective connectivity currently available. Employs a model of measured brain responses embracing their dynamic and nonlinear nature. Constructs a more realistic neuronal model of interacting cortical regions.	Daunizeau et al. 2011; Friston et al. 2003; Friston 2009; Marreiros et al. 2008; Penny et al. 2010; Stephan et al. 2005; Stephan et al. 2008; Stephan et al. 2010

Two Empirical Examples for Psycho-Physiological Interaction (PPI) Based on the Context of Online Trust

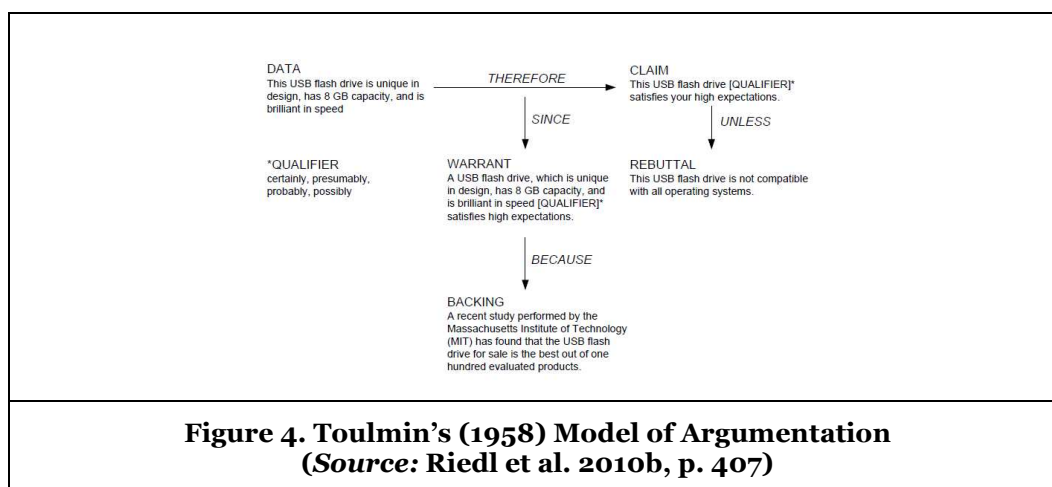
Based on a previously published study (Riedl et al. 2010b), we use PPI analysis to show the potential for integrating connectivity analyses into IS research. Two factors converge to create a unique opportunity for this research: First, a number of publications on the neural correlates of trust in an IS research context are available, enabling us to identify crucial regions of interest. Second, we have the opportunity to use a published fMRI study that has already assessed the contrast of brain activity in one condition against the brain activity in another condition (Riedl et al. 2010b).

Method and Material

The main goal of this section is to demonstrate two ways, among several possible others (see table 1), to apply connectivity analysis in IS research (here, PPI). The primary difference between the two approaches is identification of the regions of interest (or volumes of interest) for analyzing psycho-physiological interactions (Note that for simplification we use the same single participant as example for both approaches of connectivity analysis). The participant used for this investigation was randomly chosen with respect to differences in trustworthiness judgments for the given content.

1. The first way (Example 1) should illustrate a PPI analysis on the basis of an identification of two (possibly interacting) brain regions from a group analysis (see a similar procedure in Hare et al. 2009). These two brain regions are then examined within a single subject analysis by measuring psycho-physiological interaction between the two areas, in the specific context of online trust.
2. The second way (Example 2) should illustrate a more exploratory focused PPI analysis, on the basis of selecting one brain region from a single subject analysis and an ex-post examination of possibly interacting brain regions observed within a PPI analysis (see a similar procedure in Hare et al. 2010; 2011) in the context of online trust.

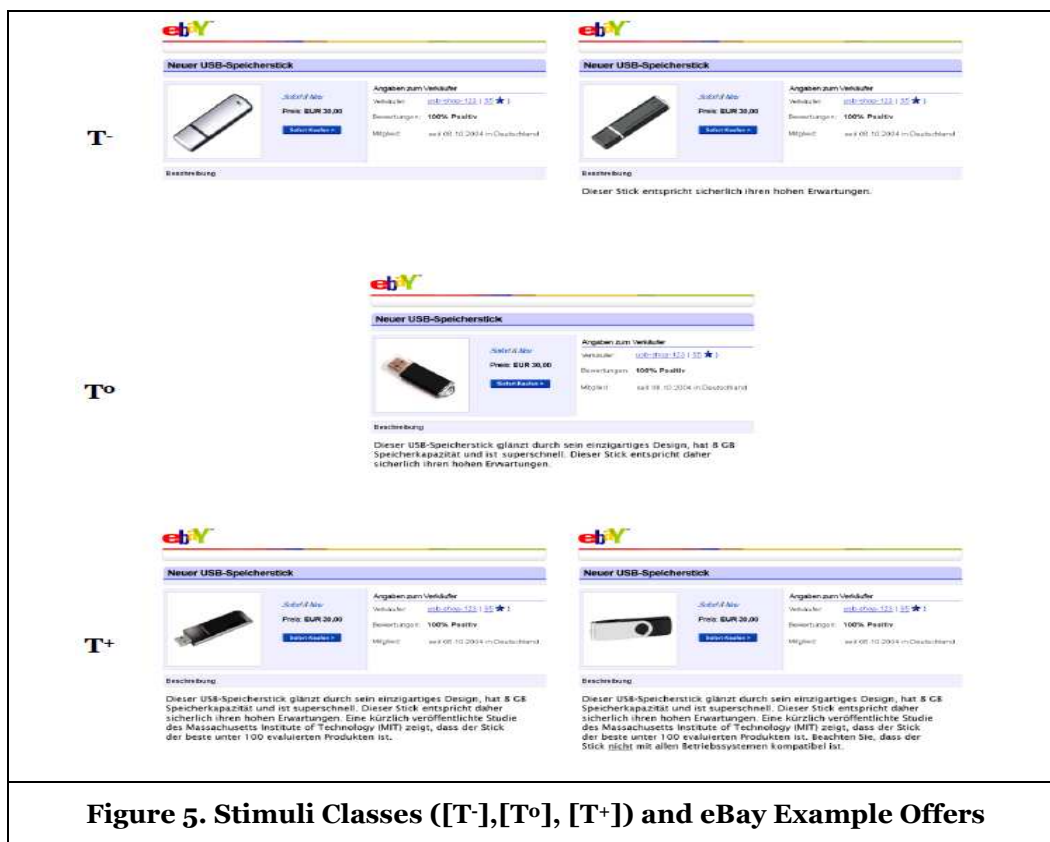
In contrast to the original publication by Riedl et al. (2010b), we do not include a focus on gender effects, but rather concentrate on main effects between different stimuli classes. The basic thrust of the Riedl et al. study was the identification of brain activation associated with the perception of both trustworthy and untrustworthy eBay offers. To provide an overview of the dataset, we briefly outline the material, sample, and data collection in the following (details are available in Riedl et al. 2010b).



First, with regard to the material, this given dataset used Toulmin's (1958) model of argumentation as a theoretical basis to create online product descriptions with a varying degree of conclusive argumentation (Figure 4). Toulmin's model has been widely used as a theoretical basis for the analysis of arguments in

scientific disciplines such as management science (e.g., Locks 1985), as well as marketing, consumer, and IS research (e.g., Gregor and Benbasat 1999; Kim and Benbasat 2006; Ye and Johnson 1995).

The elements of Toulmin's (1958) model of argumentation were embedded in a lifelike eBay website containing the following elements (see Figure 5, Riedl et al. 2010b): eBay logo, product name (New USB Flash Drive), picture of the product, selling mode, price (EUR 30.00), seller's name (usb-shop-123), seller's experience (55, a blue star indicates that the feedback score is 50 to 99), feedback (100% positive), duration and location of membership (since October 6, 2004, in Germany), and, finally, the product description, which presents the textual manipulations. In Riedl et al. (2010b), stimuli (i.e., the eBay websites) were pretested and assigned to three classes with regard to their level of trustworthiness, namely low trustworthiness [T⁻], medium trustworthiness [T⁰], and high trustworthiness [T⁺] (see Figure 5 for description and assignment). The class [T⁻] consists of stimuli without text (left) and with claim only (right); [T⁰] consists of stimuli with claim + data; [T⁺] consists of stimuli with claim + data + backing (left) and claim + data + backing + rebuttal (right). Note that the qualifier had no influence on the level of perceived trustworthiness.



Second, with regard to the sample, the fMRI study included ten male and ten female participants, all healthy and all right-handed, with $M_{age} = 31.9$ years. Standard exclusion criteria for MR examinations were applied (Savoy 2005). All participants provided written informed consent prior to the scanning sessions. Participants were informed that the examination could potentially reveal medically significant findings, and they were asked whether they would like to be notified in such a case.

Third, with regard to the fMRI experiment, the task for the participants was to state—by pressing one of two corresponding buttons on a magnetic resonance compatible response box—whether they considered an offer to be trustworthy or untrustworthy. After a twelve-second time period for processing an offer and stating the judgment, participants saw a fixation cross for three seconds. The next offer was then presented, and the displays continued in this way. The sequence of offers was pseudo-randomized for

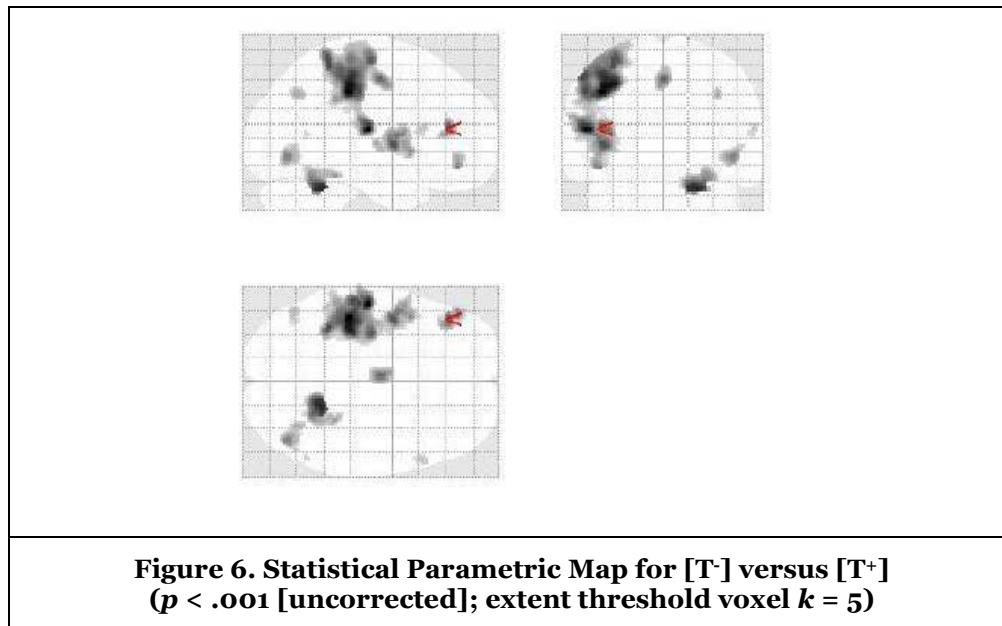
every participant, and the total number to be evaluated by each participant was 120 offers. The study was executed on a 3T scanner (Magnetom Trio, SIEMENS, Erlangen, Germany), and data analysis was conducted with the SPM8-freeware (Friston 1996; Friston et al. 1995) using MatLab as a working base. Using this method, the application followed procedures described in Huettel et al. (2009). For further details of data acquisition and analysis, see Riedl et al. (2010b).

Example 1: PPI for Extracted Regions of Interest from a Group Analysis

The aim of Example 1 is to illustrate a PPI analysis on the basis of two (possibly interacting) brain areas that were previously identified in a group analysis (Steps 1-3). These two brain regions were then examined within a single-subject analysis by measuring psycho-physiological interaction between the two brain areas in the context of online trust (Steps 4-5).

In a first step, we performed a standard General Linear Model (GLM) analysis (Friston et al. 1995; Huettel et al. 2009), noting that this approach is similar to the procedures reported in Dimoka (2010) and Riedl et al. (2010b). Within the first-level (individual) analysis, we constructed three onsets for each participant regarding the stimuli classes [T⁺], [T⁰], [T⁻] (Figure 5) in order to estimate the GLM. All onsets included information about when, and for how long, eBay offers were presented during the scan session. The estimation of the GLM was conducted by fitting a reference hemodynamic response function to each event (onset) in the observed data (Huettel et al. 2009). Also within first-level analysis, we conducted an F-Contrast (F-test: main effect of trustworthiness) and two T-contrasts (t-test) between the different stimuli classes (onsets) according to their trustworthiness, namely [T⁺] versus [T⁻] and [T⁻] versus [T⁺] (Riedl et al. 2010b). Group analysis was conducted by using one-sample t-tests based on the first-level activation contrasts.

In a second step, we generated statistical parametric maps and plotted the results for the selected contrast of [T⁻] versus [T⁺] that displayed the *t*-value of each peak voxel meeting a $p < .001$ (uncorrected) significance level with an extent threshold voxel of $k = 5$. Figure 6 shows all significant activity changes that were higher for low trustworthy offers, as compared to high trustworthy offers ([T⁻] versus [T⁺]); row 1, left: sagittal view / row 1, right: frontal view / row 2: transversal view). From this set of brain regions, we selected our two regions of interest.



In a third step, our two selected regions of interest for PPI analysis are the insula (Figure 7, sagittal view left and frontal view right) and the dorsolateral prefrontal cortex (dlPFC) (Figure 8, sagittal view left and

frontal view right). We decided to concentrate on these two regions because both brain areas have been identified in other studies on the neural correlates of trust, a main construct in IS research (for a review, see Riedl and Javor 2012). Against this background, the main goal of step 4 and step 5 was to investigate whether the activations within these two brain regions interact (PPI), or whether the insula and the dlPFC are independently activated in a trust-related context.

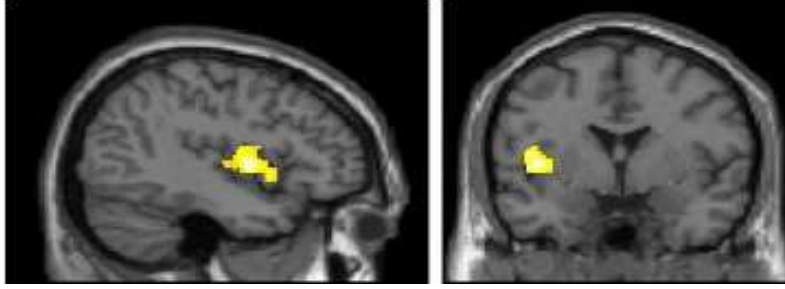


Figure 7. Insula Activity for [T⁻] versus [T⁺]

(MNI Coordinates (x, y, z) of peak voxel: -42, 0, 2; $p < .001$ [uncorrected], cluster size = 506; p -value of cluster level: $p_{\text{FalseDiscoveryRate (FDR)}} < .001$)

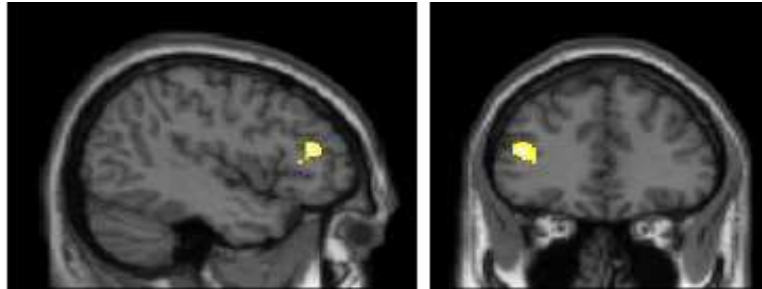
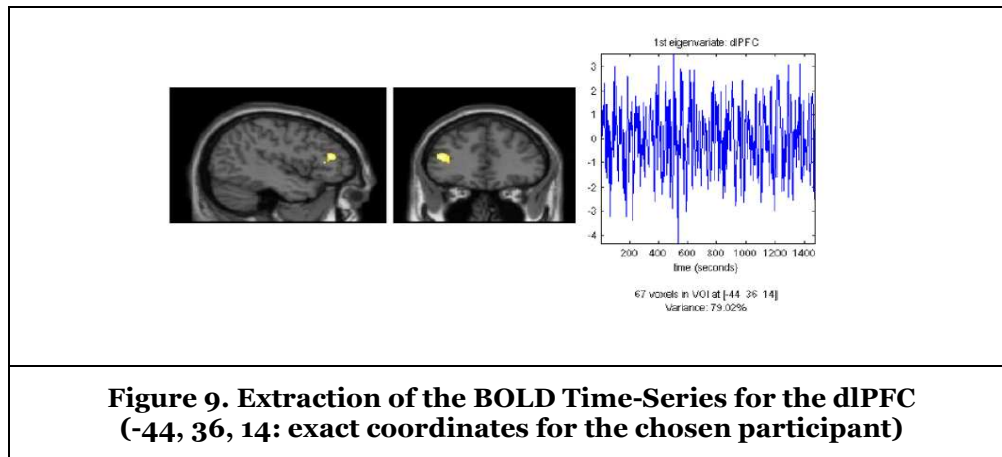


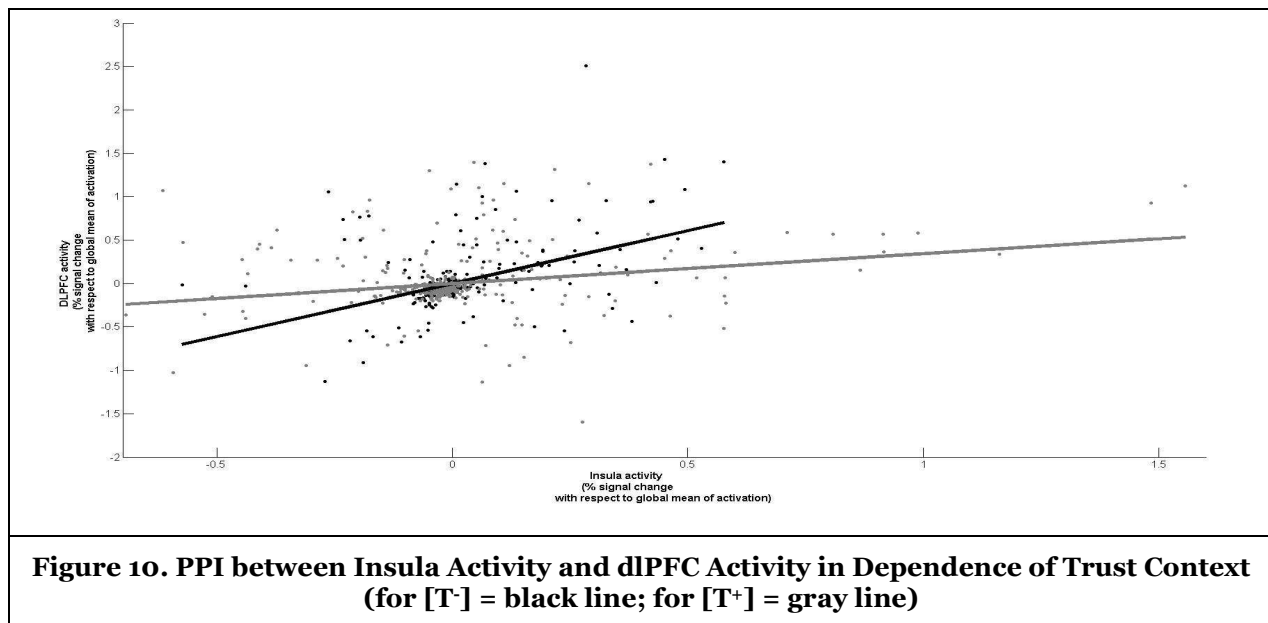
Figure 8. dlPFC Activity for [T⁻] versus [T⁺]

(MNI Coordinates (x, y, z) of peak voxel: -44, 36, 14; $p < .001$ [uncorrected], cluster size = 112; p -value of cluster level: $p_{\text{FDR}} < .05$)

In a fourth step, we analyzed the activation within the insula and the dlPFC with regard to a possible interaction (PPI) in dependence of the trustworthiness level ([T⁻], [T⁺]). To this end, we used the MNI-coordinates from the group analysis (step 3) of the selected regions of interest (insula and dlPFC) within the first level contrast ([T⁻] versus [T⁺]; $p < 0.001$ [uncorrected]; $k = 5$) of the randomly chosen participant. In detail, we applied these coordinates from the group analysis to the specific participant and extracted the Blood Oxygenation Level Dependent (BOLD) signal time-series (Huettel et al. 2009) adjusted for the main effect of trustworthiness from the source regions, namely the insula (-42, 0, 2) and dlPFC (-44, 36, 16), within a 6mm sphere around the activation peaks (insula: exact coordinates for the used region of interest for the chosen participant = -40, 0, 2 with 7 voxel within the 6mm sphere; dlPFC: exact coordinates for the used region of interest for the chosen participant = -44, 36, 14 with 67 voxel within the 6mm sphere). Figure 9 shows an example for extracting BOLD time-series based on the dlPFC.



In a fifth step, following Gitelman et al. (2003) and Friston et al. (1997), we formed the interaction term between the source regions (Insula, dlPFC) and the experimental conditions (T⁻ and T⁺). For this we separately deconvolved each extracted time course based on the model of the canonical hemodynamic response and derived the interaction term (see also the section on the basic principles of connectivity analysis). Figure 10 shows the plotted values of the interaction term (a bilinear correlation term) between source regions (insula, dlPFC) in dependence of the experimental conditions, namely [T⁻] (black line; $r_{\text{non-parametric}} = .455$, $p < .001$) and [T⁺] (gray line; $r_{\text{non-parametric}} = .237$, $p < .001$).



Summarizing our results, we observed for our exemplarily chosen participant an interaction effect between the two source regions (insula and dlPFC) and the experimental conditions ([T⁻] and [T⁺]). This PPI shows that there exists a stronger positive correlation between activation within both the insula and the dlPFC for low trustworthiness offers, compared to high trustworthiness offers. Thus, there was a stronger interaction between the insula and the dlPFC if the participant perceived low trustworthy eBay offers (black line). Furthermore, our results showed that the interaction between the two regions was still positive, but was weaker during the perception of high trustworthy offers (gray line). These results could further expand our understanding of how the brain processes negative information during decision making and is supported by Sanfey et al. (2003), who proofed the involvement of insula and dlPFC activity

in the processing of an unfair offer. Therefore, taking into account that (i) the interaction between the insula region and the dlPFC is stronger if the participant perceived low trustworthiness offers and (ii) that according to Sanfey et al. (2003) perceived unfairness accompanies with higher activity in the insula, this result of example 1 might indicate that perceived unfairness might harm trust-building processes stronger than perceived fairness positively affects trust-building.

These interactions between the two regions and experimental conditions can be interpreted in different ways (see also the section on the basic principles of connectivity analysis):

1. The influence of insula activity on dlPFC activity, or vice versa, is moderated by the differences of the experimental conditions (low and high trustworthiness).
2. The response of the dlPFC to the different experimental conditions is influenced by insula activity, or vice versa.
3. The activity in the insula and the dlPFC in dependence of the trustworthiness levels are moderated by the activity of another brain region that was not considered in connectivity analysis.

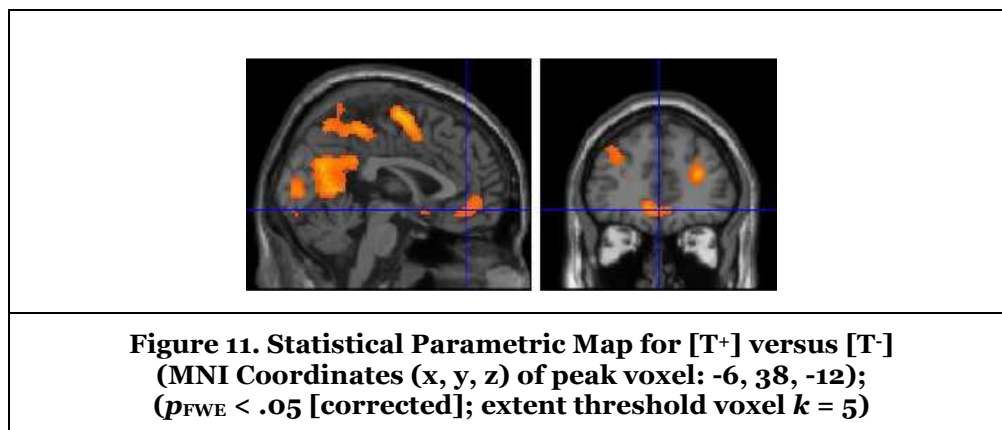
Alternative connectivity analysis (i.e., Dynamic Causal Modeling), could provide deeper insights into the interaction effect.

Example 2: PPI for Exploratory Extracted Regions of Interest from an Individual Analysis

The aim of Example 2 is to show a more exploratory focused PPI analysis. In contrast to Example 1, where we analyzed an interaction of two previously selected regions, we now illustrate an ex-post examination of possibly interacting brain regions observed within a PPI analysis in the context of online trust.

In a first step, in accord with Example 1, we performed a standard GLM analysis (Friston et al. 1995; Huettel et al. 2009). Within the first-level (individual) analysis we constructed three onsets regarding the stimuli classes $[T^+]$, $[T^0]$, and $[T^-]$ (see Figure 5) for the randomly chosen participant in order to estimate the GLM. All onsets included information about when, and for how long, eBay offers were presented during the scan session. The estimation of the GLM was conducted by fitting a reference hemodynamic response function to each event (onset) in the observed data (Huettel et al. 2009). Within first-level analysis, we conducted an F-Contrast (main effect of trustworthiness) and varying T-contrasts between the different stimuli classes (onsets) according to their trustworthiness ($[T^+]$ versus $[T^-]$ and $[T^-]$ versus $[T^+]$).

In a second step, we also generated statistical parametric maps and plotted the results for the selected contrast of $[T^+]$ versus $[T^-]$ that displayed the t -value of each peak voxel that met a $p_{FWE} < .05$ (Bonferroni corrected; Family Wise Error, FWE) significance level with an extent threshold voxel of $k = 5$. Figure 11 shows all significant activity changes that were higher for high trustworthy offers compared to low trustworthy offers ($[T^+]$ versus $[T^-]$).

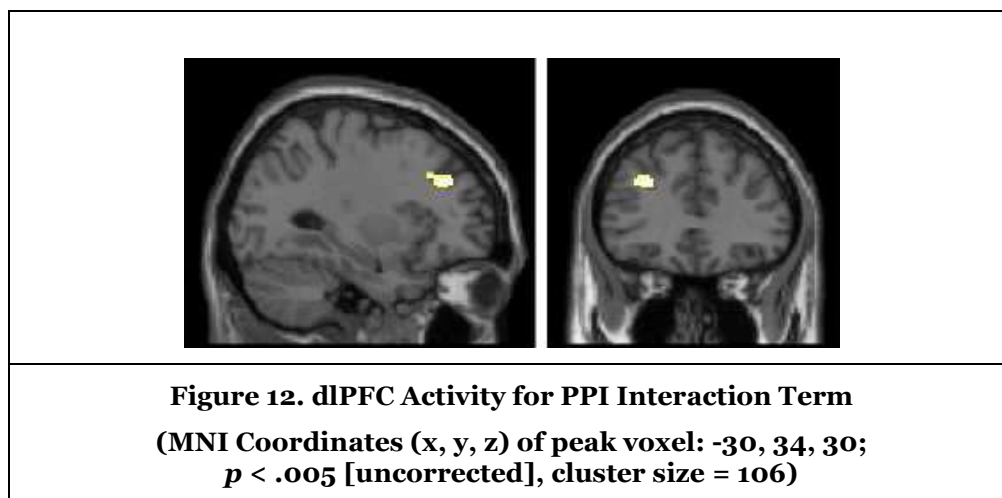


In a third step we selected, from this set of activated brain regions, the ventromedial prefrontal cortex (vmPFC) (see cross hairs in Figure 11; MNI Coordinates (x, y, z) of peak voxel: -6, 38, -12; $p < .05$ [corrected], cluster size = 183; p -value of cluster level: $p_{FDR} < .001$) as our region of interest (source region) for the PPI analysis. Taking into account that decision making is a research topic relevant for virtually all IS research questions, we decided to focus on this region because the vmPFC has often been associated with more generalized human decision making (Bechara et al. 1996, 1997, 1999; Damasio 1996), as well as with value computation (Hare et al. 2009, 2010, 2011), which is an important step in decision making. Against this background, the main goal of the following exploratory PPI analysis (steps 4-7) was to determine which regions were interacting with the vmPFC within a trust context, especially for the chosen contrast of [T-] versus [T+].

Therefore, in a fourth step we extracted the BOLD time-series adjusted for the main effect of trustworthiness from the source region, vmPFC (-6, 38, -12) within a 8mm sphere around the activation peaks.

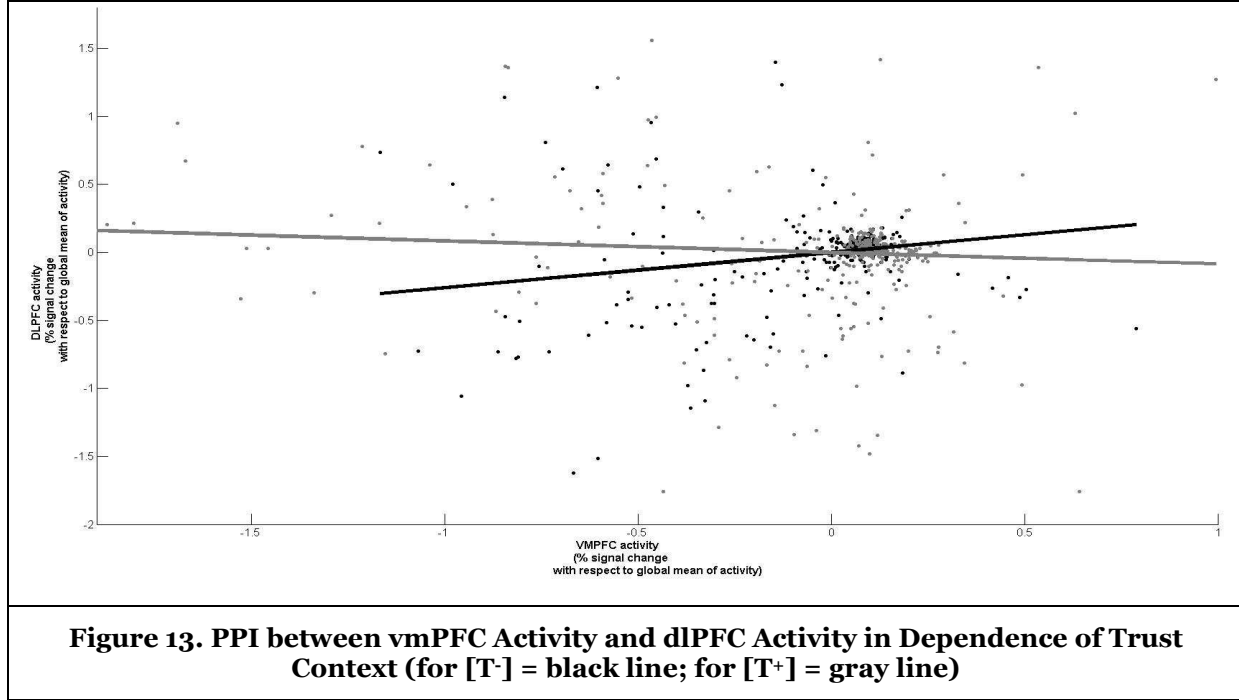
In a fifth step, following Gitelman et al. (2003) and Friston et al. (1997), we formed the interaction term between the source region (vmPFC) and the experimental conditions ([T+] and [T-]). To this end, we separately deconvolved the extracted time course based on the model of the canonical hemodynamic response and derived the interaction term.

In a sixth step, for the exemplarily chosen participant, we estimated a new GLM that included 1) an interaction between neural activity in the vmPFC and the offer presentation time for high and low trustworthy trials convolved with the canonical hemodynamic response function; 2) the original BOLD eigenvariate from the vmPFC (see an example in Figure 9); 3) a regressor specifying the offers [T+] and [T-] as an indicator convolved with the canonical hemodynamic response function; and 4) the motion parameters. Following the estimation of the GLM, a single contrast was defined for the PPI interaction term to analyze the specific brain regions that were significantly interacting with our chosen source region (vmPFC). A statistical parametric map was generated for the selected contrast of the exploratory defined PPI that displayed the t -value of each peak voxel meeting a $p < .005$ (uncorrected) significance level with an extent threshold voxel of $k = 10$ (see example in Figure 6). From this statistical parametric map we identified, among other observations, a negative correlation between our source region (vmPFC) and the dorsolateral prefrontal cortex (dlPFC) (shown in Figure 12) in dependence of the trust context ([T-] versus [T+]).



In a seventh step, repeating steps 4 and 5 from this example, we extracted the BOLD time-series adjusted for the main effect of trustworthiness from the interacting region, dlPFC (-30, 34, 30) within an 8mm sphere around the activation peaks (dlPFC: exact coordinates for the used region of interest within participant = -34, 34, 18 with 20 voxel within the 8mm sphere). Then, following Gitelman et al. (2003) and Friston et al. (1997), we formed the interaction term between the source region (vmPFC), the

interacting region (dlPFC), and the experimental conditions ([T⁺] and [T⁻]). To this end, we separately deconvolved the extracted time course based on the model of the canonical hemodynamic response, and derived the interaction term. Figure 13 shows the plotted values of the interaction term between source region (vmPFC) and dlPFC for our experimental conditions ([T⁺] (gray line; $r_{\text{non-parametric}} = -.078, p < .085$) and [T⁻] (black line; $r_{\text{non-parametric}} = .211, p < .001$)).



To summarize our exploratory results, we observed for the chosen participant an interaction effect between the source region (vmPFC) and the dlPFC for the experimental conditions ([T⁺] and [T⁻]). This PPI shows that a negative correlation exists between activation within the vmPFC and the dlPFC for high trustworthy offers (gray line), compared to a positive correlation for low trustworthy offers (black line). Thus, there is a negative interaction between the vmPFC and the dlPFC if the participant perceived the eBay offers to be highly trustworthy. In contrast, the interaction between the two regions was positive during the perception of low trustworthy offers. This result might support research on control processes (Hare et al. 2010, 2011) showing specific interacting cognitive processes (here between dlPFC and vmPFC) for value computation and decision making (Hare et al. 2009).

Analogous to Example 1, these observed interactions between a selected source region (step 3) and an interacting region within the trust context can be interpreted in a similar way (see also the section on the basic principles of connectivity analysis):

1. The influence of dlPFC activity on vmPFC activity, or vice versa, is moderated by the differences of the experimental conditions (low and high trustworthiness).
2. The response of the vmPFC to the different experimental conditions is influenced by dlPFC activity, or vice versa.
3. The activation of the vmPFC and the dlPFC in dependence of the trustworthiness levels are moderated by the activation of another brain region that was not considered in connectivity analysis. Here as well, alternative connectivity analysis (i.e., Dynamic Causal Modeling), could provide deeper insights into the interaction effect.

To conclude this section analyzing two empirical examples for psycho-physiological interaction (PPI) that are based on the context of online trust, Figure 14 gives a short summary of similar and different steps for Example 1 and Example 2.

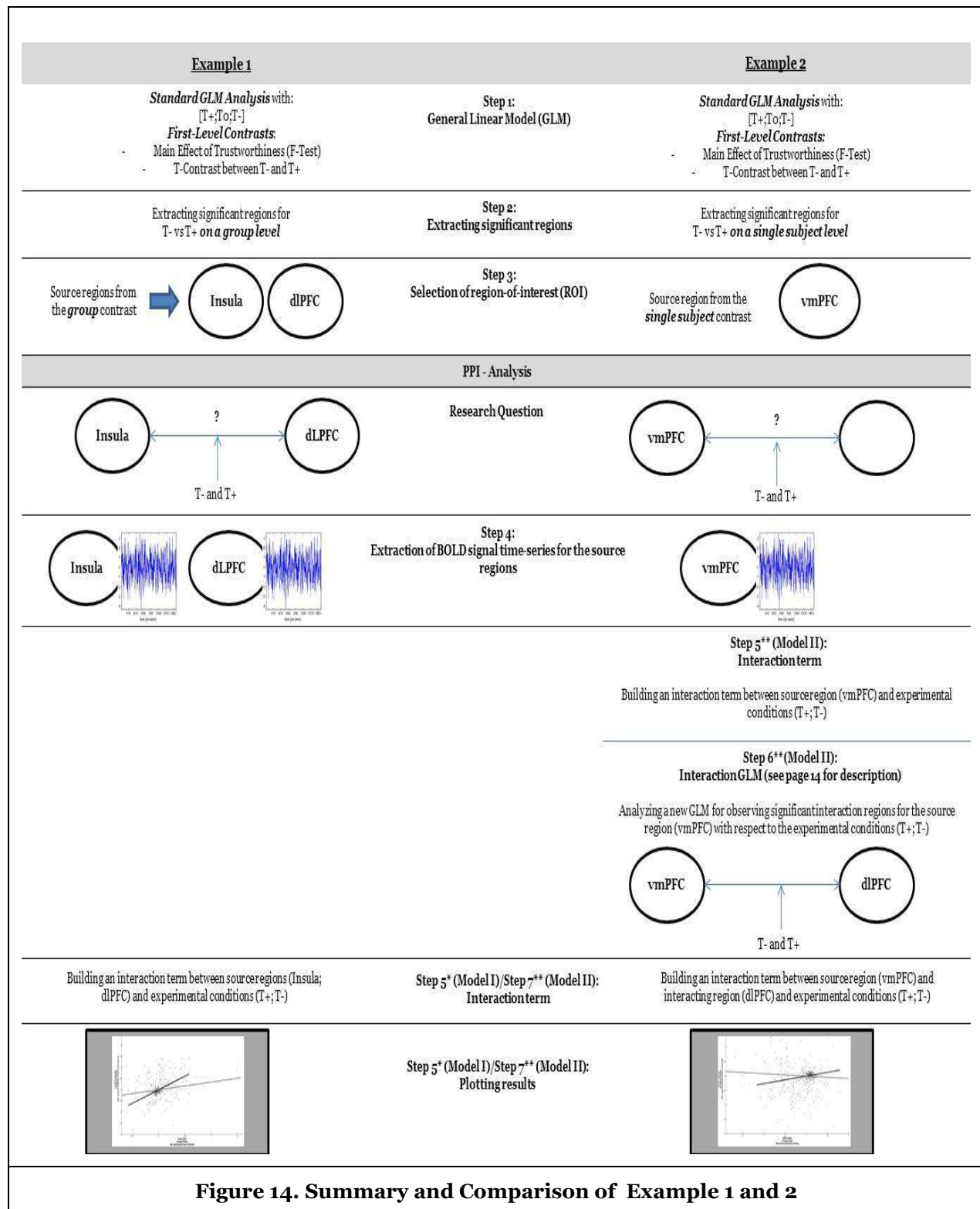


Figure 14. Summary and Comparison of Example 1 and 2

Implications and Future Research

In many scientific disciplines, research methods are either quantitative or qualitative, a fact that is particularly true for social science disciplines (e.g., Kerlinger and Lee 2000). Quantitative research—which emanates from a positivist research philosophy—aims at collecting numerical data (e.g., behavioral and neural), in order (i) to analyze it statistically and (ii) to facilitate other scientists replicating the research study. On the basis of this definition, the present article draws upon a quantitative paradigm, and contributes to the dominant paradigm in North American IS research (e.g., Chen and Hirschheim 2003). The discourse on quantitative methods, importantly, has gained considerable momentum in the IS discipline in the last decade (see, for example, a 2011 review by Riedl and Rückel on the historical development of IS research methods), and we seek to contribute to this discourse, even though both quantitative and qualitative research are important in order to obtain the most complete picture of IS phenomena. In this context, the field of NeuroIS has progressed notably during recent years—progress supported by conceptual articles (e.g., Dimoka et al. 2009, 2011, 2012; Loos et al. 2010; Riedl 2009, Riedl et al. 2010a), empirical studies (e.g., Benbasat et al. 2010; Dimoka 2010; Dimoka & Davis 2008; Riedl et al. 2010b, 2011, 2012), as well as guidelines on how to conduct fMRI studies (Dimoka 2012), that create a better understanding of the relationship between neurobiological processes and IS behavior.

This article contributes to the idea of applying cognitive neuroscience methods and tools in IS research by introducing connectivity analyses. Such analyses make possible a more detailed investigation of brain processes by explicitly taking into account that the brain works as a complex network rather than in a simple one-to-one correlation (i.e., one mental process such as trust is located in one discrete brain region). Thus, fMRI data can be analyzed and interpreted in a more comprehensive way through the use of connectivity analyses, which will lead to more reliable and valid implications for IS theories, and for corresponding practical implications. Our article opens up methodical discussions in the field of NeuroIS, outlining new ways to understand the connection between brain processes and IS behavior. The two examples draw upon an IS research context (online trust), thereby addressing one of the most prominent IS research domains. Based on our analyses, we derive the following implications for NeuroIS research:

- (1) IS researchers might re-analyze existing fMRI data sets to generate expanded information about underlying brain processes with regard to IS behavior.
- (2) Future NeuroIS studies might develop awareness of the fact that a rigorous experimental design is needed in order to apply connectivity analyses to their data (e.g., Stephan et al. 2010).
- (3) IS researchers might consider the possibility of publishing their fMRI data sets in the community to stimulate methodological discussions. The main goal of such an initiative might embrace the initialization of the necessary infrastructure and support for IS researchers who wish to publicly share their fMRI data. Against this background, such a database might become a test bed for advanced data analysis and high-performance computing approaches such as connectivity analyses (see www.openfmri.org for a similar initiative in cognitive neuroscience).

Finally, we argue that it might be beneficial to the IS community to systematically integrate the advances made in the field of NeuroIS. This could happen through the creation of respective content areas in IS outlets, particularly in peer-reviewed journals, and through a broadening of editorial boards.

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